A Combined Metaheuristic Optimization Technique for Optimal Site and Scaling of PVDG System in a Radial Distribution Network

Mansoor Alturki
Department of Electrical Engineering, College of Engineering, University of Ha'il, Saudi Arabia
m.alturki@uoh.edu.sa (corresponding author)

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ABSTRACT

Although integrating Renewable Energy Resources (RERs) into distribution systems offers benefits such as clean energy and free availability, it also introduces challenges, such as Inverse Power Flow (IPF) issues. This study proposes an efficient approach to address these issues by optimizing the placement and sizing of Photovoltaic Distributed Generation (PVDG) systems in Radial Distribution Networks (RDNs). The proposed strategy involves selecting the optimal PVDG location using the Loss Sensitivity Factor (LSF) and determining the optimal PVDG size with the Artificial Bee Colony (ABC) algorithm. This method aims to minimize active power losses and enhance the voltage profile in the investigated system. The performance of the ABC algorithm was evaluated against other optimization methods, such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA). The effectiveness of the proposed strategy was tested and validated on τηε IEEE 15-Bus and IEEE 85-Bus RDNs. The results obtained show that the ABC algorithm outperformed the other methods in reducing power losses and improving voltage profiles.

Keywords-distribution networks; optimization; meta-heuristic methods; PVDG; loss sensitivity factor

I. INTRODUCTION

Today, carbon dioxide emissions have increased dramatically around the world. Subsequently, these emissions are always considered at the top of the proposed global development spectrum in every climate change discussion that aims to stave off the rising-temperature reverberation. In tandem with the requirement to decrease carbon emissions and enhance power grid flexibility, proper orientation toward the integration of renewable resources is extremely important. The major share of these resource-based power plants is anticipated to be integrated as Distribution Generators (DGs). Moreover, it can be observed that the appropriate scaling, adaptation, and positioning of DGs lead to several important influences on the distribution network, including voltage stability and power grid quality enhancements. Various studies have been conducted to handle optimal DG installation issues when integrated into the distribution system using several optimization methods, including analytical and metaheuristic methods. Selecting the suitable placement and determining the appropriate size of DG systems to reduce grid power losses and improve voltage stability have attracted the interest of several researchers.

Different methods have been presented, ranging from analytical-based methods [1, 2] to metaheuristic techniques [3-5], to deal with this task and to further address possible solutions. In [1], a sensitivity factor method based on power loss reduction was proposed to select the best size and allocation of DG systems. This technique was applied to the IEEE 33-Bus RDN. The Loss Sensitivity Factor (LSF) was introduced in [2] to select the placement of Photovoltaic (PV) and Wind Turbine (WT) systems coupled with an Energy Storage System (ESS) in the IEEE 33-Bus RDN. The main objective of this method was to minimize the grid power losses.

In recent years, metaheuristic algorithms such as Particle Swarm Optimization (PSO) [3], Whale Optimization Algorithm (WOA) [4, 6], Genetic Algorithm (GA) [5, 7], Firefly Algorithm (FA) [8], Invasive Weed Optimization (IWO) [9], Backtracking Search Algorithm (BSA) [10], Garra Rufa Optimization (GRO) [11], Harris Hawks Optimizer (HHO) [12], Grey Wolf Optimizer (GWO) [13], Artificial Bee Colony (ABC) [14], and Bat Algorithm (BA) [15] have attracted substantial attention to optimally integrate DG systems in distribution networks. This is due to their ability to handle complex and nonlinear problems compared to conventional methods. In [3], PSO was employed to identify the optimal placement and sizing of two DG units, which were integrated with Energy Storage Systems (ESSs) within the IEEE 33-Bus RDN. The main objective of this method was to reduce system losses and enhance the voltage profile. In [4, 5] the WOA was proposed to determine optimal DG integration solutions based on technical and economic aspects. This algorithm was tested on IEEE 33-Bus and IEEE 69-Bus RDNs. In [6], GA was developed to optimally locate the DG system on a 6-Bus RDN. This method was based not only on power losses and voltage enhancement under different load conditions but also on the phase angle jump changes.

Fuzzy inference systems have been used to properly manage energy flow. However, in [7], this algorithm was proposed to find the optimal size of a DG system, while the LSF method was investigated to properly select its placement. The main objective of this method was to reduce power losses and improve the voltage profile of the IEEE 15-bus network and the Nigerian 11 KV feeder. In [8], FA was used to find the appropriate allocation and the best size of the PVBES system. This method was based not only on technical and economic concerns but also on the environmental aspects of power losses, costs, and emissions reduction. This method was applied to the IEEE 30-Bus distribution network. To properly integrate the DG system into the IEEE 33-Bus and IEEE 69-Bus systems, the IWO and BSA algorithms were proposed in [9, 10], respectively, to minimize power losses, reduce energy costs, and enhance voltage stability under different load models. The aim of [11-12] was to reduce power losses and improve the voltage profiles of the IEEE 30-Bus, IEEE 14-Bus, IEEE 33-Bus, and IEEE 69-Bus systems. Additionally, a modified GWO based on the fuzzy decision technique was introduced in [13] for the optimal sizing of a PV-wind system integrated into the IEEE 33-Bus network. A multi-objective function based on reducing power losses and improving system reliability was also introduced. In addition, sensitivity analysis was used to select the optimal placement of the aforementioned DG systems.

The primary objective of this study was to investigate the effectiveness and robustness of the LSF method in determining the optimal allocation of DG units while using the ABC algorithm for their optimal sizing.

II. PROBLEM DESCRIPTION

The main objective of this study is to reduce the total active power losses and enhance the voltage profile of the RDN. To achieve this, a PVDG unit was used at one of the RDN buses, as illustrated by the simple two-bus example in Figure 1. Consider a distribution line (m, m+1) that connects two buses, where bus m is the sending end and bus m+1 is the receiving end. The active and reactive power flows through the branch (m, m+1) are represented by Pm and Qm, respectively. The active and reactive power consumed by the load at bus m are denoted by PLm and QLm, respectively. The resistance and reactance of the branch (m, m+1) are given by $R(m, m+1)$ and $X(m, m+1)$, respectively, while the voltages at buses m and m+1 are denoted by V_m and V_{m+1}, respectively.

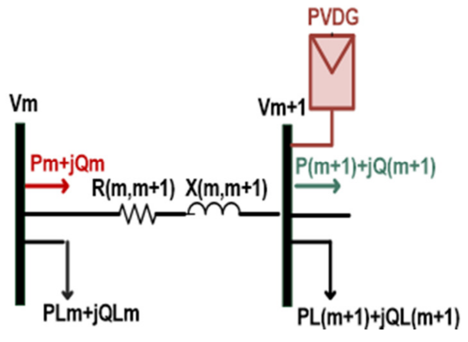

Fig. 1. Single line of an RDN.

A. *Objective function*

Using the forward/backward sweep method, the active power losses $P_{loss}(m, m+1)$ and the reactive power losses $Q_{loss}(m, m+1)$ of the branch (m,m+1) can be expressed using (1) and (2) [13].

$$P_{loss}(m, m+1) = R(m, m+1) \times \left(\frac{Pm^2+Qm^2}{|Vm^2|}\right) \quad (1)$$

$$Q_{loss}(m, m+1) = X(m, m+1) \times \left(\frac{Pm^2+Qm^2}{|Vm^2|}\right) \quad (2)$$

Hence, the objective function f_{obj} can be written using [16]:

$$f_{obj} = \min\ (P_{Tloss}) \quad (3)$$

where

$$P_{Tloss} = \sum_{m=1}^{N-1} P_{loss}(m, m+1) \quad (4)$$

B. *Constraints*

To resolve the above-mentioned objective function, some constraints should be taken into account.

1) *PVDG Allocation Constraint*

The appropriate placement of the PVDG system should be considered as shown in (5).

$$2 \le PVDG_{placement} \le N \quad (5)$$

where N represents the total bus number. The first node is defined as the slack bus.

2) *PVDG Capacity Constraint*

$$P_{PVDG}{}^{min} \le P_{PVDG} \le P_{PVDG}{}^{max} \quad (6)$$

3) *Voltage Profile Constraint*

$$V^{min} \le V_i \le V^{max} \quad (7)$$

In this study, $0.9\ p.u \le V_i \le 1.1\ p.u$

III. PROPOSED OPTIMIZATION METHOD

A. *LSF Technique*

The selection of the optimal position of the DG system is achieved using the LSF method due to its simplicity and its advantages in terms of search space reduction for the optimization process [2]. LSF is one of the main indices used in the selection of the best placement of DGs within power distribution networks, as it quantifies the sensitivity of active power losses in the network relative to changes in active power injection at specific buses.

As given in (8), the LSF at node m is calculated as the partial derivative of the power losses in branch (m-1, m) with respect to the active power injected at this node.

$$LSF\ (m) = \frac{\partial P_{loss}(m-1,m)}{\partial Pm} = R(m-1, m)\left(2\frac{Pm}{V_m^2}\right) \quad (8)$$

Once the LSFs for all candidate buses are calculated, they are ranked in ascending order. Then, the DGs will be placed on the buses where the LSF values are highest. This means that small injections of real power at these buses will result in the most significant reduction in total distribution system losses.

B. Optimization Methods

The second step of this study consists of identifying the optimal scaling of the DG system that is integrated into the optimal allocation, selected using the LSF method. To achieve this objective, several optimization techniques have been investigated and presented in the literature. The selection of an appropriate optimization method is considered a critical step for a nonlinear system under several operating constraints. To overcome system non-linearity problems, nature-inspired evolutionary algorithms have been widely used due to their ability to deal with complex and nonlinear problems.

In this study, three optimization algorithms were applied to select the proper capacity of the PVDG system, including the PSO, GA, and ABC techniques, and a comparative study of them is presented.

1) PSO Algorithm

The PSO technique has been widely used to resolve nonlinear optimization issues due to its implementation simplicity and flexibility [17]. This algorithm is inspired by the animals' social behavior, especially that of birds, to reach their target of food. With the interaction of both social and self-experience, and with continuously updating their position and velocity, a swarm of birds named particles moves towards their optimal target. The PSO algorithm starts with randomly generating the initial population, called a swarm (group of particles) as presented in (9).

$$X_a^j = X_a^{min} + \propto (X_a^{max} - X_a^{min}) \quad (9)$$

where $\propto \in (0,1), j = 1, \ldots, P$ and $a = 1, \ldots, d$. P and d are the population size and the problem dimension, respectively. X_a^{max} and X_a^{min} are the limits of the a^{th} decision variable. $X^j = [X_1^j, X_2^j, \ldots, X_d^j]$ represents the j^{th} particle of the population P. Then, this population is modified at every iteration k by updating the position X^j and the velocity V^j of every particle as shown in (10) and (11) [18].

$$X_{k+1}^j = X_k^j + V_{k+1}^j \quad (10)$$

$$V_{k+1}^j = w \times V_k^j + c_1 r_1 (p_{best,k}^j - X_k^j) + c_2 r_2 (g_{best,k} - X_k^j) \quad (11)$$

where $r_1, r_2 \epsilon (0,1)$. V_k^j and X_k^j represent the velocity and the position of the j^{th} particle at the k^{th} iteration, respectively. $p_{best,k}^j$ represents the best position of the j^{th} particle, $g_{best,k}$ denotes the global best position of particles at the k^{th} iteration, c_1 and c_2 are the acceleration coefficients, and w represents the inertia weight, which is given by [19]:

$$w = w_{max} - \frac{w_{max} - w_{min}}{k_{max}} \times k \quad (12)$$

The PSO pseudo-code is presented in Algorithm 1.

```
Algorithm 1: Particle Swarm Optimization
1: Initialization of PSO parameters (P, d,
   w, X_a^min, X_a^max, c_1, c_2, r_1, r_2, w_max, w_min,
   k_max)
2: Generation of the initial population
   for each particle j = 1 to P do
     for a = 1 to d do
       Generate a random position X_a^j
       using (9)
     end for
     Evaluate fitness for the j^th particle
     using (3)
     Update p_best^j and then g_best
   end for
3: Identification of the best PSO solution
    while k < k_max do
      for j=1 to P do
        if f(X^j) < f(p_best^j) then
          Update p_best^j = X^j
        end if
        if f(p_best^j) < f(g_best) then
          Update g_best = p_best^j
        end if
      end for
   end while
```

2) GA Technique

Over the past two decades, GA has attracted significant attention for addressing nonlinear and complex optimization problems. It has found extensive applications across various research and engineering domains, particularly for determining the optimal placement and capacity of PVDG units in the RDNs [20]. This algorithm is inspired by the principles of natural and biological evolution to evaluate and refine its results [21]. It operates through four main stages: initial population generation, selection, crossover, and mutation. Specifically, the process begins with generating a random initial population, as described in [22]. This population consists of a group of individuals known as chromosomes. Subsequently, genetic operations, such as selection, crossover, and mutation, are applied during each production step to evolve and improve the optimal solutions. The generation of chromosomes for the initial population is carried out randomly, as given by (13).

$$Y_a^j = Y_a^{min} + \beta (Y_a^{max} - Y_a^{min}) \quad (13)$$

where $\beta \in (0,1)$, $j = 1, \ldots, P$ and $a = 1, \ldots, d$. P and d are the population size and the problem dimension, respectively. Y_a^{max} and Y_a^{min} define the upper and lower bounds of the a^{th} decision variable. Note that $Y^j = [Y_1^j, Y_2^j, \ldots, Y_d^j]$ represents the j^{th} individual of the population. The GA pseudo-code is presented in Algorithm 2.

```
Algorithm 2: Genetic Algorithm (GA)
1: Initialization of P, d, Y_b^min, Y_b^max, and
   iter_max
2: Generation of the initial population
   for j=1 to P do
     for a=1 to d do
       Generate a random position Y_a^j
     end for
```

```
    Evaluation of the fitness f for the
    j^th individual
  end for
3: Identification of the best GA solution
  while iter < iter_max do
    application of crossover operator
    application of mutation operator
    Greedy selection
  End while
```

C. ABC Algorithm

The ABC algorithm was introduced to optimally size the PVDG system due to its simplicity and its ability to deal with complex and non-linear optimization problems. The principle of this algorithm is significantly inspired by the behavior of honey bees and their interactions to converge toward their optimal target [4]. Among several population-based algorithms, the ABC algorithm has been widely applied when handling various optimization problems. Due to its advantages in terms of fewer control parameter requirements, great versatility, and good resilience [23], the ABC algorithm has been used in various engineering fields, notably the optimal DG system installation in the distribution network.

It is noteworthy to highlight that bee colonies are categorized into three types, namely employed, onlooker, and scout bees [23]. The ABC algorithm starts with a random population initialization, which is composed of a group of variables called food sources A^i, as shown in (14) [24]. Then, a new solution B is generated randomly using (15) [24].

$$A_j^i = A_j^{min} + \theta \times \left(A_j^{max} - A_j^{min}\right) \qquad (14)$$

$$B_j{}^i = A_j^i + \rho \times \left(A_j^i - A_j^k\right), \qquad (15)$$

where $k = 1,..,P$, $i \neq k$, $\theta, \rho \in (0,1)$, $i = 1,\dots,P$ and $j = 1,\dots,d$. P and d present the size of the population and problem dimension, respectively. A_j^{max} and A_j^{min} define the maximum and minimum limits of the j^{th} decision variable, respectively. In general, to find the optimal food source, a fitness ratio Fr and a selection probability Pr are applied as shown in (16) and (17) [24].

$$Fr_i = \begin{cases} \frac{1}{1+F(A^i)} & if \quad F(A^i) > 0 \\ 1 + \left|F(A^i)\right| & otherwise \end{cases} \qquad (16)$$

$$Pr_i = \frac{Fr_i}{\sum_{i=1}^{popF} Fr_i} \qquad (17)$$

```
Algorithm 3: Artificial Bee Colony
1:  Initialization of ABC parameters (P,
    d, A_j^min, A_j^max, iter_max)
2:  Generation of the initial population
    for i=1 to P do
      for j=1 to d do
        Generate a random position A_j^i
      end for
    end for
3:  for i=1 to P do
    Generate a new solution
      for j=1 to dim do
        Generate a random position B_j^i
      end for
      if F(B_j^i) < F(A_j^i) then
        A_j^i = B_j
        k = 0
      else
        k = k + 1
      end if
    end for
    Evaluation of the fitness function and
    Pr
    if rand < Pr_i then
      Update a new solution B^i
    end if
    if F(B_j^i) < F(A_j^i) then
      A_j^i = B_j
      k = 0
    else
      k = k + 1
    end if
    if max(k) > iter_max
      Generate a new food source
    end if
    Determination of the optimal solution
```

IV. SIMULATION RESULTS

To demonstrate the effectiveness and applicability of the proposed strategy for selecting the proper scaling and position of the PVDG system, two RDNs were investigated, namely the IEEE 15-Bus and IEEE 85-Bus systems. As it has been shown, the appropriate allocation is identified using the LSF method, while the proper scaling of the PVDG system is selected using the ABC algorithm. As mentioned before, this study aimed to reduce system power losses and enhance its voltage profile. Figure 2 presents the IEEE 15-Bus single-line diagram. This RDN is composed of 15 nodes and 14 lines. The total active and reactive power, consumed by loads, are 1226.4 kW and 1251.11 kVAR [13], respectively. This distribution network is characterized by the 11 kV base voltage and the initial power losses are approximately 61.79 kW.

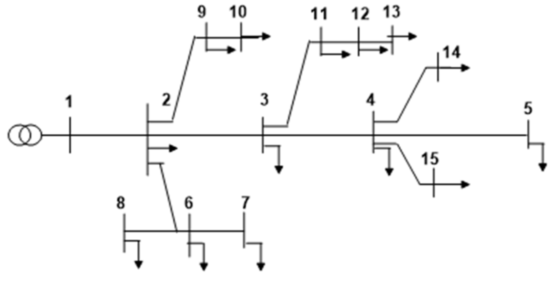

Fig. 2. IEEE 15-bus RDN.

Figure 3 shows the network topology of the IEEE 85-Bus system. This RDN consists of 85 nodes and 84 lines. Its total load demand is around 2550.56 kW [25], and the total reactive power load is 2595.16 kVAR [25]. The system base voltage is 11 kV and the initial active power losses are 315.7 kW.

A. LSF Method

The LSF technique was used to properly integrate the DG system in the RDN and optimally obtain the allocation that leads to the lowest active power losses. This method consists of selecting the sensitive node that further decreases active power losses. The highest LSF value is obtained to select the optimal placement for the DG system. Figures 4 and 5 illustrate the LSF values of all buses for the IEEE 15-Bus and 85-Bus systems, respectively. According to Figure 4, the proper position of the PVDG system in the IEEE 15-Bus system is the second node. This bus indicates the highest LSF value. However, according to Figure 5, node number 8 is selected to be the optimal location for the PVDG unit in the IEEE 85-Bus.

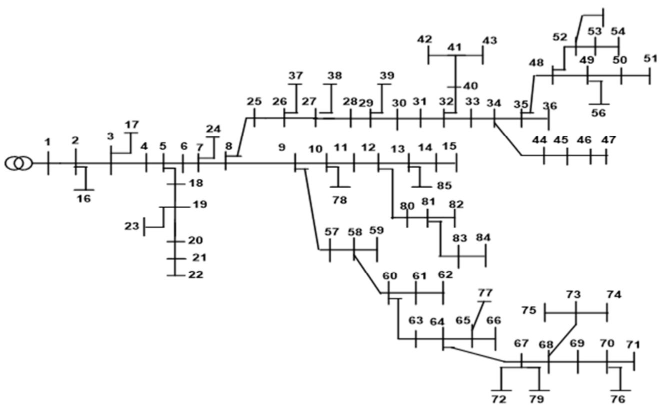

Fig. 3. IEEE 85-Bus RDN.

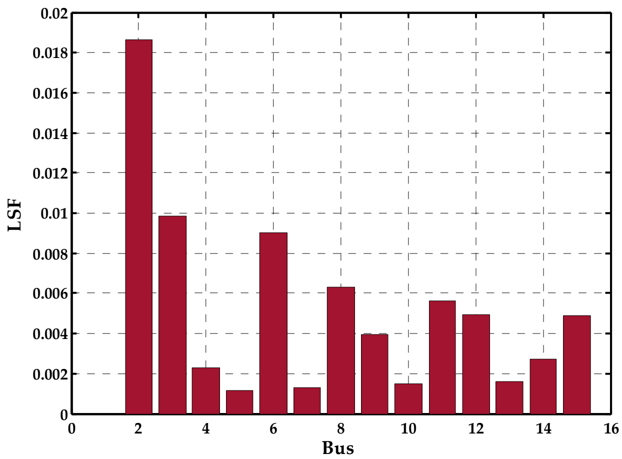

Fig. 4. LSF values for the IEEE 15-Bus distribution network.

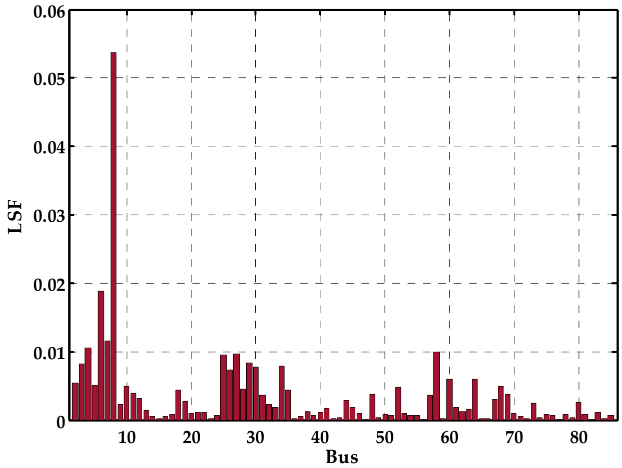

Fig. 5. LSF values for the IEEE 85-Bus distribution network.

B. Optimal Scaling of the PVDG System

After selecting the appropriate allocation of the PVDG system in the RDN, its optimal capacity was investigated according to the constraint presented in (17).

$$5kW \leq P_{PVDG} \leq 1MW \tag{17}$$

Three optimization techniques were applied and compared to correctly choose the optimal scaling of the DG unit to further decrease the real power losses and improve the voltage profile in the system.

1) IEEE 15-Bus RDN

Figure 6 shows the convergence characteristics of the objective function using the three investigated optimization techniques. According to this figure, it is noteworthy that compared to the other optimization methods, the ABC algorithm converges much faster to the appropriate solution. According to this comparison, it can be verified and demonstrated that the proposed ABC technique outperformed the GA and PSO algorithms in terms of power loss reduction.

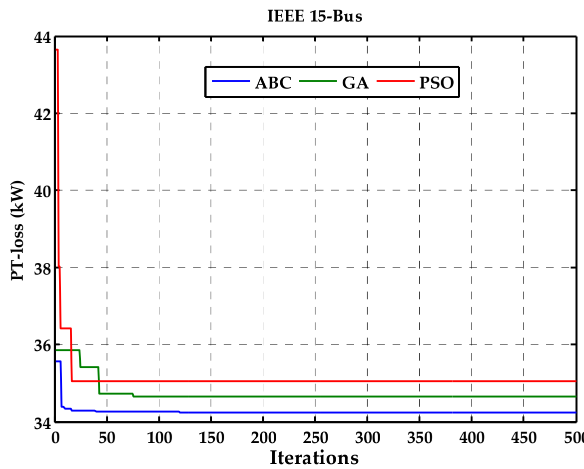

Fig. 6. Convergence characteristics of the objective function.

Figure 7 shows the voltage profile of the IEEE 15-Bus after integrating the PVDG system in the second node and using the three optimization techniques.

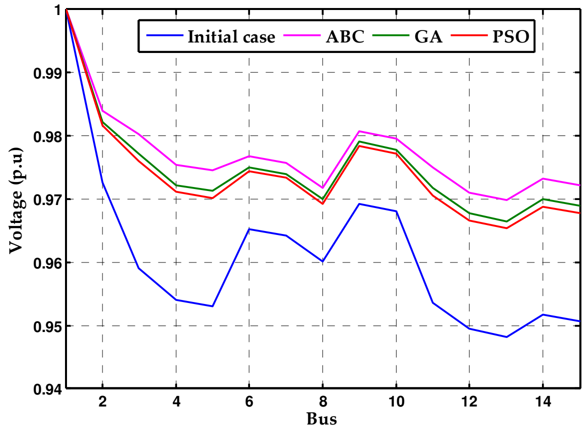

Fig. 7. Voltage profile.

According to Figure 7, it can be observed that by applying the proposed ABC algorithm, the voltage profile of the RDN was significantly improved compared to the initial case, GA, and PSO. Furthermore, this improvement was especially shown in node number 13, where the voltage magnitude was increased from 0.949 p.u. to 0.97 p.u. using ABC. However, the voltage magnitude at this node was increased only from 0.949 p.u. to 0.965 p.u. and from 0.949 p.u. to 0.966 p.u. using the PSO and GA, respectively.

Figure 8 illustrates line power losses before and after the PVDG system allocation to the optimal placement using the ABC, GA, and PSO algorithms. The results show that active power losses in the system branches are significantly reduced after the incorporation of the PVDG unit. For instance, the first and tenth lines were drastically dropped from 34 kW to 18 kW and from 2 kW to 1.44 kW, respectively, using the ABC algorithm. This demonstrates the efficiency and robustness of the proposed strategy that combines LSF and ABC techniques in power loss reduction.

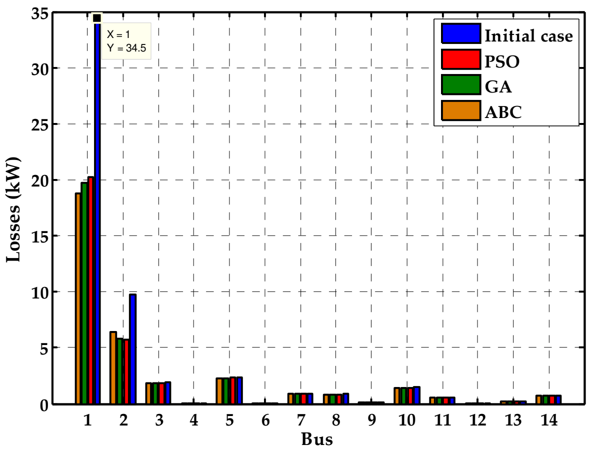

Fig. 8. Lines' power losses.

C. IEEE 85-Bus RDN

The appropriate position of the PVDG system obtained by the LSF method in the IEEE 85-Bus is at bus 8. The optimal capacity of this system was selected according to the proposed ABC method and the constraint presented in (18).

$$5kW \leq P_{PVDG} \leq 3\ MW \quad (18)$$

A comparative study was carried out to demonstrate the efficiency of this technique. Figure 9 presents the convergence characteristics of these optimization techniques. According to Figure 9, it can be observed that compared to other optimization methods, the ABC algorithm converged much faster to the appropriate solution. These results show that the proposed ABC technique outperformed GA and PSO in terms of power loss reduction and convergence speed.

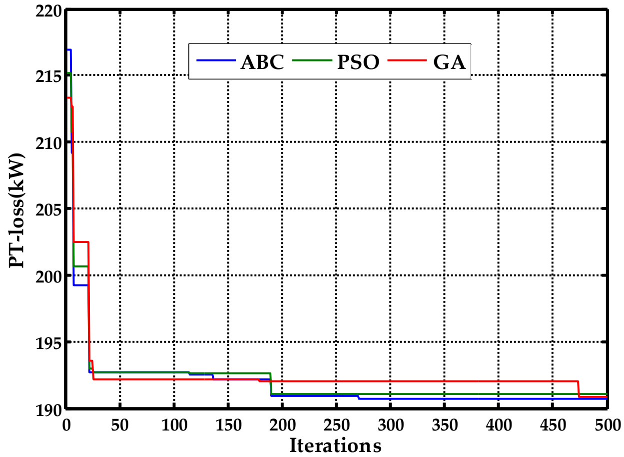

Fig. 9. Convergence characteristic of the objective function.

Figure 10 presents the voltage profile of the IEEE 85-Bus system after integrating the PVDG system at node 8 and after applying the three investigated optimization techniques. The results show that by applying the proposed ABC algorithm, the voltage profile was significantly improved compared to the initial case, GA, and PSO.

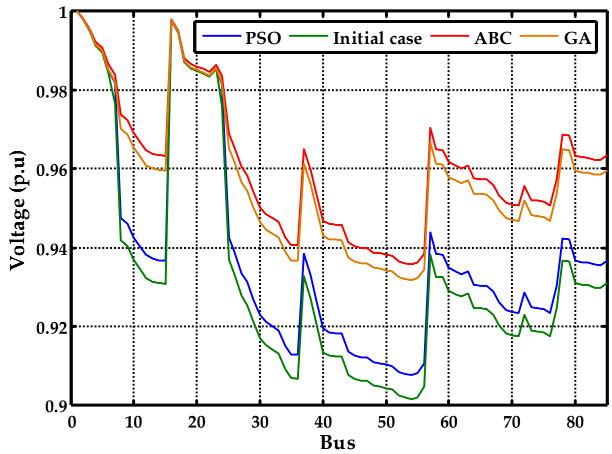

Fig. 10. Voltage profile.

Moreover, this improvement was especially shown for the case of node 55 which was improved from 0.902 p.u. to 0.936 p.u. using ABC compared to 0.932 p.u. and 0.908 p.u. using GA and PSO, respectively.

Figures 11 to 14 show line power losses before and after the allocation of the PVDG system in the optimal placement using the ABC, GA, and PSO algorithms. It can be observed that line active power losses were significantly reduced after integrating the PVDG unit. The first seven nodes were drastically reduced. Taking the case of nodes number 7 and 57, power losses dropped from 92 kW and 6.5 kW to 40 kW and 5.5 kW using the ABC algorithm. This demonstrates the efficiency and robustness of the proposed strategy combining LSF and ABC in power loss reduction.

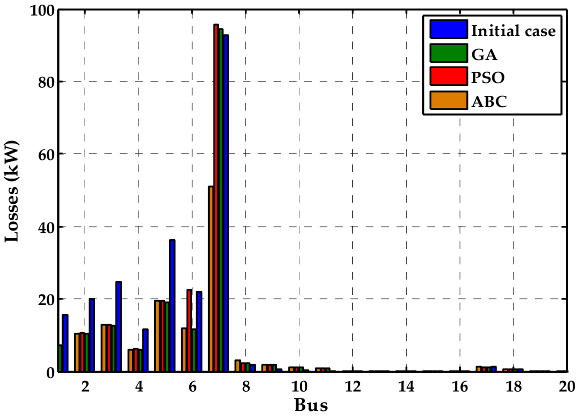

Fig. 11. Lines power losses from bus 1 to bus 20.

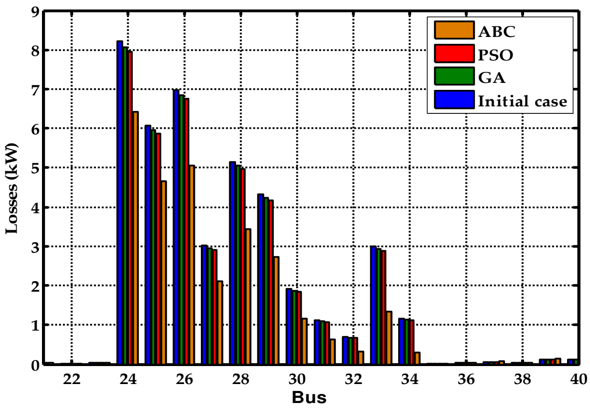

Fig. 12. Lines power losses from bus 21 to bus 40.

D. Results Discussion

Based on the simulation results, it can be observed that the proposed strategy based on LSF and ABC is an efficient method for finding the optimal capacity and site of PVDG units. The efficiency of this strategy can be further demonstrated through the comparative study presented in Tables I and II.

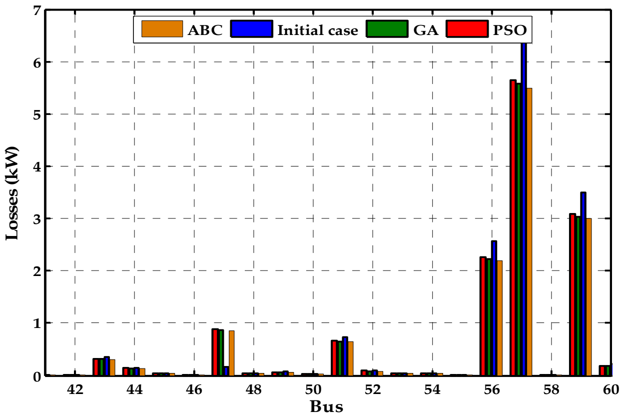

Fig. 13. Lines power losses from bus 41 to bus 60.

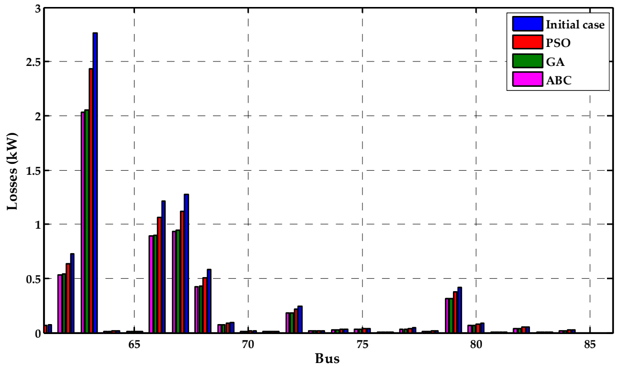

Fig. 14. Lines power losses from bus 61 to bus 85.

TABLE I. COMPARATIVE RESULTS FOR THE IEEE 15-BUS SYSTEM

Algorithm	ABC	GA	PSO	[26]	[27]
Initial losses [kW]	61.79				
Best size [MW]	0.93	0.9	0.6	-	0.675
Bus	2	3	3	3	6
PT_{losses}[kW]	34.25	34.45	35.1	37.86	45.8
Losses reduction [%]	44.5	44.2	43	38.7	25.8
V_{min} [p.u.]	0.97	0.965	0.967	0.967	0.95

TABLE II. COMPARATIVE RESULTS FOR THE IEEE 85-BUS SYSTEM

Algorithm	ABC	GA	PSO	[28]	[29]
Initial losses [kW]	315.7				
Best size [MW]	2.34	2.26	2.1	0.91	2.4
Bus	9	8	8	54	51
PT_{losses}[kW]	190.7	191	1921	227.1	242.9
Losses reduction [%]	40	39.4	39.1	28	23
V_{min} [p.u.]	0.936	0.932	0.908	0.91	0.945

Based on these tables and the other simulation results, it can be concluded that the proposed technique demonstrates superior performance in minimizing power losses and improving the voltage profile. In addition, it provides the minimum power losses compared to the other optimization algorithms. Moreover, it can be observed that after the integration of the PVDG units in the optimal placement, voltage magnitude at all buses is maintained within satisfied limits [V_{min}, V_{max}], for both systems.

The validity and effectiveness of the proposed strategy to solve the optimal sizing and placement of DGs in RDNs were evaluated using the IEEE 15-Bus and IEEE 85-Bus RDNs under the rated values. The simulation results showed the effectiveness of the proposed optimization technique in providing the best optimal solutions. The ABC algorithm is a powerful tool for solving complex mixed-integer problems due to its ability to escape local optima. However, when integrating renewable energy sources such as PV systems, varying solar irradiation throughout the day can influence the optimal operation of DGs. Therefore, it is imperative to maintain optimal RDN performance under random irradiations. To mitigate the effects of varying solar irradiation, Energy Storage Systems (ESSs) can be integrated with DGs.

Future studies may focus on developing real-time optimization algorithms to adjust the power output of ESSs-based DGs in response to varying solar radiations.

V. CONCLUSION

The main objective of this study was to minimize power losses and enhance the voltage profile in an RDN. A robust metaheuristic method was presented to optimally select the position of the PVDG system and to properly size it. The IEEE 15-Bus and 85-Bus RDNs were considered due to their considerable radial network topologies and their free data availability. It is well known that introducing a DG system into the electrical network can prevent the IPF issue and, as a result, reduce the system power losses. In addition, as shown in the simulation results, the system voltage magnitudes of the proposed RDNs were considered weak in the base case because some nodes were near the acceptable boundary limits, which were 0.9 p.u. in this case.

To address these issues, the LSF method was employed to determine the optimal placement of PVDG units in the RDNs. Once the ideal location was identified, the ABC algorithm was used to determine the optimal capacity of these systems. The effectiveness of the proposed technique was evaluated by comparing it with other optimization algorithms, including PSO and GA. The simulation results showed that the proposed strategy combining LSF and ABC outperformed the other methods, providing superior results in reducing power losses, improving the voltage profile, and mitigating reverse power flow.

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